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Student mobility experience: Fast-track to the first job or nice-to-have?

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Abstract

Purpose — This study evaluates whether student mobility programmes, including student exchange, internships, and community service, facilitate faster school-to-work transitions among Indonesian graduates, addressing limited causal evidence in developing-country contexts.

Method — The analysis draws on nationally representative Sakernas 2024 data and employs a propensity score matching framework to address non-random programme participation and obtain more reliable estimates of treatment effects across different mobility pathways.

Findings — Participation in all student mobility programmes significantly shortens the waiting time for the first job. Student exchange yields the largest effect, followed by internships and community service, indicating heterogeneous impacts across programme types. These differences reflect the varying nature of skills and experiences developed in each programme. The results further suggest that mobility experiences enhance employability by acting as credible signals of graduates' skills, adaptability, and work readiness

Implications — Expanding access and improving the alignment of mobility programmes with labor market needs, as well as integrating them into formal curricula, can strengthen graduate employability and improve labor market matching efficiency.

Originality — This study provides the first comparative and causal evidence on multiple student mobility pathways in Indonesia, using nationally representative data, and offers new insights into the role of experiential learning in accelerating early-career outcomes.

Keywords: Student Mobility, School-to-work Transition, National Labour Force Survey (Sakernas), Propensity Score Matching.

JEL Classification: C21; E24; I23; J24; J64

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Introduction

Getting a decent job quickly is often the main ambition of fresh graduates, but it largely depends on the quality of their human capital, which signals their potential productivity to employers. Graduate job competition depends not only on academic hard skills but also on strong soft skills and relevant experience. However, both skills are difficult to cultivate solely in class due to scarce resources. To address this gap, universities and governments worldwide have increasingly adopted Student Mobility (SM) programs of enrich students' competencies beyond the classroom.

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In Indonesia, for instance, SM programmes have been formalised under the *Merdeka Belajar – Kampus Merdeka* (MBKM) framework, encompassing initiatives such as the Indonesian International Student Mobility Awards (IISMA) and *Pertukaran Mahasiswa Merdeka* (PMM) for student exchanges, *Studi Independen Bersertifikat* (MSIB) for internships, and *Kuliah Kerja Nyata* (KKN) for community service programs. Since its launch in 2020 (now '*Kampus Berdampak*'), the Indonesian government has invested more than IDR 5 trillion in these initiatives (Ministry of Finance, 2022). Yet regardless of institutional context, an empirical question remains underexplored especially in the context of developing countries like Indonesia: whether participation in SM programmes effectively reduces graduates' waiting time for their first job. According to human capital theory (Schultz, 1961; Becker, 1962), investments in education and training enhance individuals' productive capacity, thereby improving their outcomes in the labour market.

SM programmes represent one such investment, as they expose students to environments beyond the conventional classroom. However, human capital theory alone does not fully explain how these programmes generate skill development. Experiential learning theory (Kolb, 1984) provides the underlying mechanism: learning occurs through a cyclical process of concrete experience, reflective observation, abstract conceptualisation, and active experimentation.

In the context of SM programmes, students engage directly in real-world settings, whether in workplaces, universities, or communities, and it is through this experiential cycle that both technical and soft skills relevant to the labour market are formed (Virtue, 2022; Pianda et al., 2024; Sari and Norasikin, 2025). Employers tend to assess candidates' productivity through observable signals, as they rarely have direct access to candidates' true abilities. Academic credentials such as GPA are commonly used for this purpose, though they may not reliably capture practical or softskills, especially when grade inflation undermines their credibility as a signal.

Signaling theory (Arrow, 1973; Spence, 1973) suggests that participation in SM programmes can serve as a complemantary signal, providing employers with richer information to evaluate candidates more accurately, which may ultimately improve candidates' labor market outcomes, including a shorter waiting time for their first job. Figure 1 illustrates the conceptual framework linking SM programmes and employment outcomes. The SM programmes often help students develop essential skills such as teamwork and collaboration, adaptability, leadership and professionalism, problem-solving and critical thinking, as well as communication and interpersonal skills (Kapareliotis, Voutsina and Patsiotis, 2019; Sadeghi, Wiers-Jenssen and Thørrisen, 2022; Bennett, Knight and Li, 2023; Mtawa, Fongwa and Wilson-Strydom, 2021; Musa, Nurhayati and Boriboon, 2025).

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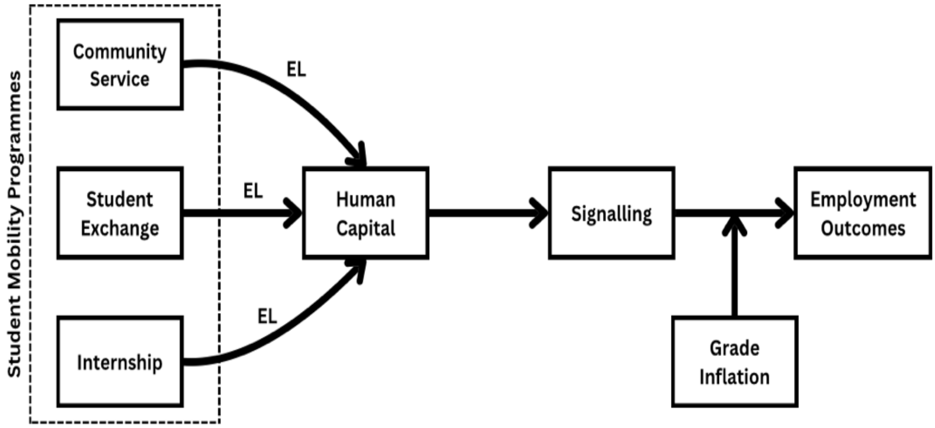
Figure 1. Conceptual Framework: Student Mobility and Employment Outcomes



Notes: EL stands for Experiental Learning. Source: Authors' visualisation based on previous literature.

Community service programmes, on the other hand, strengthen participants' competencies in social environments. Working directly with communities that often face resource constraints, students learn to negotiate with local stakeholders and practise community-grounded problem-solving, empathy, and grassroots leadership (Reed-Bouley, Wernli and Sather, 2012; Fede, Gorman and Cimini, 2018; Mtawa, Fongwa and Wilson-Strydom, 2021; Omar et al., 2022; Gbadamosi and Oladele, 2025; Ikendi et al., 2025). Internship programmes place students in workplace settings with deadlines, supervisors and deliverables, aspects that are less emphasised in the other two SM programmes.

As a result, students are expected to gain stronger workplace readiness, practical job skills, and credible professional experience (Kapareliotis, Voutsina, and Patsiotis, 2019; Musa, Nurhayati, and Boriboon, 2025b). Figure 2 illustrates the general competencies developed through participation in SM programmes. Globally, previous studies have examined the effectiveness of SM programmes on fresh graduates' waiting time for their first job, but the findings remain inconclusive. For internship programmes, Klein and Weiss (2011), Verhaest and Baert (2018), and found no significant effects, whereas Di Meglio et al. (2022) and Margaryan et al. (2022) reported that internships help applicants secure jobs more quickly.

Similarly, evidence on student exchange is mixed, with some studies reporting no effects (Van Mol, Caarls and Souto-Otero, 2021; Wiers-Jenssen and Støren, 2021), others finding positive effects (Di Pietro, 2013; d'Hombres and Schnepf, 2021; Pozniak, Cultrera and Vermeylen, 2025), and some documenting negative effects under specific conditions such as economic crisis (Iriondo, 2020). Empirical evidence on community service context remains relatively limited, although existing studies generally suggest positive effects (Matthews, Dorfman and Wu, 2015; Ma Hok-ka, Chan Wing-fung and Chan Cheung-ming, 2016).

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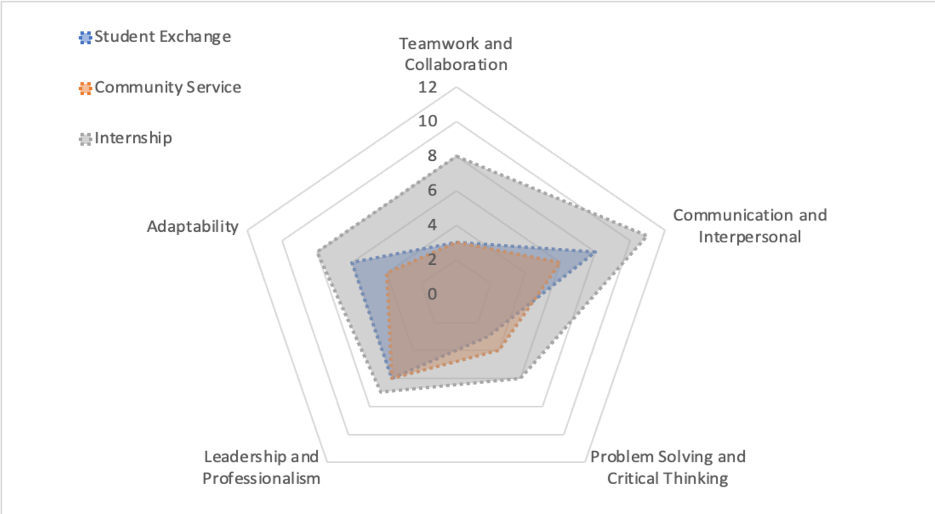
Figure 2. General Competencies in Student Mobility Programmes



Notes: Appendix 1 summarises previous studies that serve as the source for this chart. Source: Authors' visualisation based on previous studies.

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Empirical evidence on community service context remains relatively limited, although existing studies generally suggest positive effects (Matthews, Dorfman, and Wu, 2015; Ma Hok-ka, Chan Wing-fung, and Chan Cheung-ming, 2016).
Despite these mixed findings, both human capital theory and experiental learning theory, as mentioned earlier, suggest that participation in SM programmes enhance individuals' competencies through learning and experience, while signalling theory posits that participation in such programmes provides observable signals of otherwise unobservable attributes to employers.

Therefore, this study hypothesises that participation in SM programmes (student exchange, community service, and internships) reduces graduates' waiting time for their first job, with the effect size potentially varying across programme types. This study seeks to contribute to the existing literature by examining the causal effect of SM programmes participation on graduates' waiting time for their first job in Indonesia. To the best of our knowledge, this study is the first to address this gap in Indonesia. Waiting time for a first job is a key labour market indicator, as prolonged joblessness leads to skill loss, poorer health, family stress, and lower future earnings (Nichols, Mitchell and Lindner, 2013; De Fraja, Lemos and Rockey, 2021; Deschacht and Vansteenkiste, 2021).

By providing empirical evidence on this issue, the study offers valuable insights for policymakers and higher education institutions seeking to improve the design and implementation of SM programmes. Furthermore, the main methodological challenge in measuring the impact of SM programmes is the risk of selection bias, as participation in such programmes is not random.

In other words, participants and non-participants may differ in their underlying characteristics, which can lead to biased estimates if standard regression methods such as Ordinary Least Squares (OLS) are applied. Consequently, any observed impact on waiting time for the first job may reflect these pre-existing differences rather than the effect of the SM programmes themselves. To address this concern, this study applies Propensity Score Matching (PSM) to account for observable characteristics (e.g gender, age, marital status, technological access and literacy, region, and field of study) that may influence both programme participation and employment outcomes, using data from the 2024 National Labour Force Survey (*Sakernas*).

Our results indicated that OLS estimates tend to overstate the effects of SM programmes on graduates' waiting time for their first job. After applying PSM, we found that, overall, graduates who participate in SM programmes were more likely to secure employment more quickly than their non-participating peers. More specifcally, individuals who participated in a student exchange program obtained their first job approximately 40 days faster than those who did not. Meanwhile, participants in internships and community service activities obtained their first job around 38 days and 35 days faster than their non-participating counterparts, respectively.

The paper is structured as follows: the "Methodology" section describes the data, variables, method, and assumptions employed in the study. The "Results and Discussions" section presents the outcomes of the research and offers an analytical discussion of them. Finally, the study concluded with a "Conclusion and Policy Recommendations" section that summarises the key findings and suggestions for future research, and provides policy recommendations.

Methodology

The data for this study is from the August 2024 wave of the National Labour Force Survey (*Sakernas*), which is a biannual and nationally representative survey of the labour force done by Statistics Indonesia (BPS). *Sakernas* is the primary source for labour force participation and employment outcomes. It reports detailed information on employment status, education, demographics, and labour market characteristics for individuals aged 15 and older. The poll uses a stratified sampling strategy to make sure that the results are representative at both the national and provincial levels.

The August 2024 round is different since it includes information about each person's engagement in SM programmes while in college, like student exchange, internships, and community service activities. This data provides significant insights for evaluating the impact of SM programmes on waiting time for their first job in Indonesia. Furthermore, in accordance with the study's purpose and the implementation of the *Merdeka Belajar–Kampus Merdeka* (MBKM) programmes, we restrict the sample to individuals who obtained a bachelor's degree in 2020 or subsequently. We measure the main outcome as the time it takes a graduate to get their first job after finishing a bachelor's degree. In Sakernas, someone is considered "employed" if they did any income-generating activity for at least one hour during the reference week.

This definition is broad and encompasses both formal and informal employment, as well as non-standard work arrangements. While this tells us how quickly graduates enter the labour market, it does not necessarily mean they find a good or well-matched job.

Instead, it reflects the speed of entry into the labour market, which may involve trade-offs between employment timing and job quality. For student mobility (SM) programmes, we create three dummy variables, each indicating whether an individual participated in a student exchange, an internship, or a community service program during their studies. Unfortunately, the data do not allow us to separate national from international programmes, nor do they show how long graduates spent in these activities. The other operational descriptions of variables can be found in Appendix 2. We use the propensity score matching (PSM) method to estimate how SM programmes affect first job waiting time. PSM is a good fit here because it reduces the selection problem in observational data (Rosenbaum and Rubin, 1983).

The selection problem arises when students decide for themselves whether to join a program, meaning participation is not random. While alternative methods such as instrumental variables (IV) or difference-in-differences (DiD) can also address selection bias, they require either a valid instrument or longitudinal data with pre- and post-treatment observations, conditions not met by our cross-sectional dataset. PSM, by contrast, balances treated and control groups on observed covariates without requiring these data, making it well-suited to our setting. If this issue is not addressed, estimates of the treatment effect could be misleading, since any difference in outcome might simply reflect pre-existing differences between groups rather than the causal impact of the SM programmes.

The control groups for each SM program are constructed using non-participants with propensity scores similar to those of the participants. In practice, this involves first estimating the probability of participation in an SM program using observed baseline characteristics and then matching each participant with one or more comparable non-participants. Following previous literature on this topic and given our data availability, we use several pre-treatment covariates that can potentially influence an individual's participation in SM programmes and their first job waiting time: gender, age, marital status, type of school, field of study, region, province, participation in training, and technological skills. The propensity score is estimated using a probit model, which can be written as:

$$(D_i = 1 \mid X_i) = \Phi(\beta_0 + \beta_1 X_i) \tag{1}$$

where $\Phi(\cdot)$ denotes the cumulative distribution function of the standard normal distribution, and X_i represents the vector of baseline covariates for the individual, i as mentioned earlier. The estimated propensity scores are then used to match treated $(D_i = 1)$ and untreated individuals to construct an appropriate control group for each program. To isolate the influence of the other SM programmes on participation and outcome, we use the two other programmes as covariates for each probit model.

Then, we estimate the average treatment effect for the treated (ATT) for each PSM model to find the average effect of a SM program (e.g., student exchange) on those individuals who ultimately participated in the program. Or mathematically, ATT is defined as $E[Y(1) - Y(0)|D_i = 1]$. In our main analysis, we rely on the Kernel Matching (KM) algorithm.

For robustness, we also re-estimate the model using alternative matching procedures such as nearest neighbour, calliper, and radius matching. Unlike these algorithms, which generally pair each treated observation with the closest control observation (except for local linear matching, LLM), KM constructs counterfactual outcomes using all available control observations.

Each control is weighted according to the similarity of its propensity score to that of the treated unit. The main advantage of KM lies in its efficiency: by incorporating more information from the sample, it reduces the variance of the estimates. However, this efficiency gain may come at the cost of increased bias if poor-quality matches are included (Linden & Samuels, 2022; Caliendo and Kopeinig, 2008). Smith and Todd (2005) formalise KM as a weighted regression of the counterfactual outcome on a constant, where the kernel weights depend on the distance in propensity scores between treated and control units.

When the kernel is symmetric, nonnegative, and unimodal, greater weight is placed on control observations that are closer in propensity score to the treated individual, while more distant controls receive lower weight. This procedure yields an estimate of the counterfactual mean. Building on this foundation, Chen et al. (2025) further establish the asymptotic normality and consistency of kernel matching estimators for both ATE and ATT, providing a more rigorous theoretical basis for their use in causal inference. The kernel weight for the treated individual i and the control individual j can be expressed as follows:

$$w(i,j) = \frac{K\left(\frac{p(x_j)-p(x_i)}{h}\right)}{\sum_{k:D_k=0} K\left(\frac{p(x_k)-p(x_i)}{h}\right)} \quad (2)$$

Where $p(x_i)$ and $p(x_j)$ denote the propensity scores of treated individual i and control individual j, respectively; h is the bandwidth parameter that determines the smoothness of the kernel function; and $K(\cdot)$ is the chosen kernel function (e.g., Gaussian). The denominator serves as a normalisation factor to ensure that the weights sum to one across all controls. For estimation purposes, we use the *psmatch2* command in Stata, which was developed by Leuven and Sianesi (2003).

There are two fundamental assumptions of the PSM method: unconfoundedness (also known as the conditional independence assumption (CIA) or selection on observables) and common support (or overlap assumption). The first assumption is that “the difference in outcomes between treated and comparison individuals with the same value of pre-treatment covariates is attributable to treatment” (Gertler et al., 2016a; Liau, M.Y.Q., et al, 2024).

It is a very strong assumption and challenging because it depends on the quality of data on hand, and it cannot be tested. In our case, we use several reputable studies on this topic to identify the determinants of participation in SM programmes and first-job waiting time as the outcome. We believe that the most important pre-treatment characteristics are included in our models.

Under the common support assumption, each treated unit must be matched with a non-treated one; thus, individuals with similar characteristics (X) have a positive probability (P) of being both participants and non-participants (Gertler et al., 2016). The common support assumption can be written as $0 < P(X) < 1$. There are some procedures for checking this assumption, which are mentioned by several researchers. However, following Granja and Visentin (2024), we use the straightforward procedure by using visualisation graphs, which show the density distribution of the propensity score for both groups.

Results and Discussions

Table 1 presents the descriptive statistics for participants and non-participants across the student mobility (SM) programmes: student exchange, community service, and internships. Participation levels vary across programmes, with 329 individuals in the student exchange programme, 3,509 in community service, and 5,450 in internships.

Table 1. Summary Statistics of Participants and Non-participants

	Participant			Non-Participant			Difference (8)-(5) (SE)
	Obs	Mean	SE	Obs	Mean	SE	
	(4)	(5)	(6)	(7)	(8)	(9)	
Student Exchange Program							
Gender (if female)	329	0.674	0.025	13,263	0.627	0.004	-0.046 (0.026)**
Age	329	25.887	0.297	13,263	27.367	0.056	1.480 (0.364)***
Marital Status (if married)	329	0.188	0.021	13,263	0.282	0.003	0.094 (0.025)***
Type of School (if private)	329	0.407	0.027	13,263	0.474	0.004	0.067 (0.027)**
Training (if yes)	329	0.583	0.027	13,263	0.546	0.004	-0.037 (0.027)
On-going training (if yes)	329	0.072	0.014	13,263	0.037	0.001	-0.035 (0.010)***
Computer use (if yes)	329	0.768	0.023	13,263	0.762	0.003	-0.006 (0.023)
Smartphone use (if yes)	329	0.987	0.000	13,263	0.994	0.006	0.007 (0.004)*
Internet use (if yes)	329	0.978	0.007	13,263	0.986	0.000	0.007 (0.006)
Region (if rural)	329	0.525	0.027	13,263	0.373	0.004	-0.152 (0.027)***
Community Services Program							
Gender (if female)	3,509	0.650	0.008	10,083	0.622	0.005	-0.028 (0.009)***
Age	3,509	24.154	0.072	10,083	28.090	0.070	2.940 (0.126)***
Marital Status (if married)	3,509	0.156	0.006	10,083	0.324	0.004	0.167 (0.09)***
Type of School (if private)	3,509	0.433	0.008	10,083	0.487	0.005	0.054 (0.009)***
Training (if yes)	3,509	0.572	0.004	10,083	0.539	0.005	-0.033 (0.000)***
On-going training (if yes)	3,509	0.051	0.004	10,083	0.341	0.002	-0.017 (0.000)***
Computer use (if yes)	3,509	0.791	0.007	10,083	0.753	0.004	-0.038 (0.000)*
Smartphone use (if yes)	3,509	0.995	0.001	10,083	0.995	0.000	0.000 (0.014)
Internet use (if yes)	3,509	0.988	0.002	10,083	0.986	0.011	-0.018 (0.420)
Region (if rural)	3,509	0.399	0.082	10,083	0.369	0.005	-0.029 (0.002)***

	Participant			Non-Participant			Difference (8)-(5) (SE)
	Obs	Mean	SE	Obs	Mean	SE	
	(4)	(5)	(6)	(7)	(8)	(9)	
Internship Program							
Gender (if female)	5,450	0.639	0.006	8,142	0.621	0.005	-0.017 (0.008)**
Age	5,450	25.225	0.057	8,142	28.742	0.081	3.517 (0.110)***
Marital Status (if married)	5,450	0.155	0.004	8,142	0.364	0.005	0.208 (0.007)***
Type of School (if private)	5,450	0.468	0.005	8,142	0.475	0.006	0.007 (0.008)
Training (if yes)	5,450	0.563	0.006	8,142	0.536	0.005	-0.026 (0.008)***
On-going training (if yes)	5,450	0.049	0.002	8,142	0.031	0.001	-0.018 (0.003)***
Computer use (if yes)	5,450	0.785	0.005	8,142	0.747	0.004	-0.037 (0.007)***
Smartphone use (if yes)	5,450	0.994	0.000	8,142	0.994	0.000	-0.000 (0.001)
Internet use (if yes)	5,450	0.988	0.001	8,142	0.985	0.001	-0.003 (0.22)
Region (if rural)	5,450	0.381	0.007	8,142	0.375	0.005	-0.006 (0.008)

Source: Processed by Author

The relatively small number of student exchange participants compared to non-participants (329 versus 13,263) likely reflects the barriers students face in accessing such programmes. These include financial constraints, competitive selection processes, academic eligibility requirements, and limited institutional capacity in terms of available partnerships and slots (Simek and Stewart, 2024). Students from lower socioeconomic backgrounds may be particularly disadvantaged in accessing these opportunities, raising equity concerns about who benefits from SM programmes. In the student exchange programme, about 67 percent of participants are female, their average age is around 25 years, and most are unmarried.

Participants also report relatively high access to technology and digital skills. Compared to non-participants, they differ significantly across most demographic and socioeconomic characteristics, except for training, computer use, and internet use, where no meaningful differences are observed. Community service program participants also exhibit distinct characteristics relative to non-participants. They are more likely to be female, younger, and less likely to be married, with a higher share coming from public schools. Participants are more likely to have completed training but less likely to be engaged in ongoing training. Digital access is high in both groups, though participants show a slightly higher rate of computer use. Internet and smartphone use, however, do not differ significantly between the two groups. Finally, participants are somewhat less likely to reside in rural areas.

Similarly, internship program participants differ notably from non-participants. They are more likely to be female, younger, and unmarried, and of have attended public schools. Participants are also more likely to have completed training, but less likely to be involved in ongoing training. They report higher rates of computer use, although smartphone and internet use remain nearly universal across both groups.

No significant differences are observed in terms of rural residence. Taken together, these descriptive patterns suggest that participants in SM programmes differ significantly from non-participants across several demographic, educational, and digital access characteristics, underscoring the importance of incorporating these factors as baseline covariates in the PSM method. Table 2 presents marginal effects from the probit estimates, capturing the effects of individual and institutional factors on the odds of participating in student mobility schemes. The report already considers the presence of other treatment variables in the model. Regarding demographic characteristics, age has contrasting effects.

Table 2. Marginal Effects Estimation for Each Student Mobility Programmes (Probit Results)

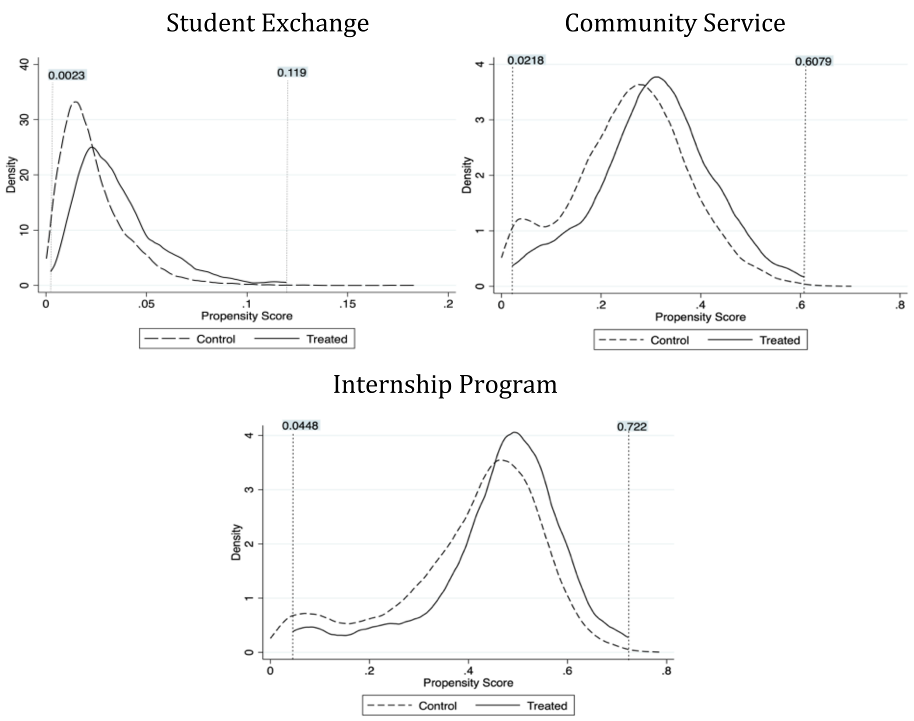
Variables	(1) Dependent Variable: Pr(Student Exchange=1)	(2) Dependent Variable: Pr(Community Service=1)	(3) Dependent Variable: Pr(Internship=1)
Gender (if female)	0.005 (0.002)	0.001 (0.007)	-0.005 (0.008)
Age	0.000 (0.000)	-0.007*** (0.001)	-0.013*** (0.001)
Marital Status (if married)	-0.003 (0.004)	-0.013 (0.009)	-0.077*** (0.010)
Type of School (if private)	-0.003 (0.003)	-0.020*** (0.007)	0.026*** (0.008)
Training (if yes)	0.002 (0.003)	0.024*** (0.006)	0.023*** (0.007)
On-going training (if yes)	0.007 (0.005)	0.022 (0.016)	0.071*** (0.019)
Computer use (if yes)	0.002 (0.003)	0.021*** (0.008)	0.014 (0.009)
Smartphone use (if yes)	-0.019 (0.019)	-0.044 (0.056)	-0.014 (0.056)
Internet use (if yes)	0.001 (0.014)	0.009 (0.031)	0.010 (0.034)
Region (if rural)	0.010*** (0.003)	0.018*** (0.007)	0.008 (0.008)
Student Exchange (if yes)	-	0.150*** (0.020)	0.264*** (0.034)
Community Service (if yes)	0.024*** (0.003)	-	0.418*** (0.06)
Internship (if yes)	0.034*** (0.004)	0.330*** (0.005)	-

Notes: The dummy variables representing fields of study and provinces are not displayed in the main table but are reported in Table A4 of the Appendix for clarity and simplicity. Standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1. Source: Authors' calculations from Sakernas 2024.

For community service, an additional year of age significantly reduces the likelihood of participation by 0.7 percentage points at 1 percent ($p<0.01$). Similarly, for internships, each additional year of age decreases the probability of participation by 1.3 percentage points significantly at 1 percent ($p<0.01$), confirming that younger students are more likely to participate in these two programmes. By contrast, age has no significant effect on student exchanges but shows a positive sign, which indicates that older students, particularly those in later years of attendance, may participate in exchanges as they are in more favourable standing in terms of prerequisites, language skills, and course appropriateness.

In addition, being married significantly reduces internship by 7.7 percentage points ($p<0.01$), reinforcing the idea that family responsibilities constrain opportunities for experiential learning. Meanwhile, gender does not have noticeable effects between programmes, which means that if other variables are held constant, female and male students both experience equal chances of being involved. Coming from a private school lowers the likelihood of community service by 2.0 percentage points but raises the likelihood of internships by 2.6 percentage points, a significant effect. Students from rural areas are more likely to join exchanges by about 1.0 percentage points and internships by 0.8 percentage points. This may reflect program outreach or stronger incentives for rural youth to take part. As mentioned earlier, the common support assumption requires that participants and non-participants share overlapping characteristics, ensuring that each treated individual can be meaningfully compared with similar untreated individuals.

Figure 3. Distribution of Propensity Scores for Treatment and Control Groups



Source: Authors' calculations and visualisations.

We calculate the propensity scores for each SM Program using the estimated probit model above. Figure 3 displays the density distributions of propensity scores for both groups in each SM program. As expected, in all programmes, the distribution of propensity scores for treated units is more skewed to the left relative to controls. Importantly, our results indicate that the common support assumption is satisfied, with 100 percent of treated units in all programmes falling within the common support region. In other words, all individuals who participated in each SM program have comparable untreated counterparts with similar propensity scores, and thus, no evidence of a lack of common support is observed.

We then conduct balancing tests before and after matching to evaluate whether the distribution of observed covariates between participants and non-participants becomes more comparable for each SM program (Table 3, Table 4, Table 5). This step ensures that any remaining differences in waiting time for the first job can be attributed to program participation rather than pre-treatment characteristics. Tables 3–5 present the results. The findings indicate a clear reduction in bias following matching (see column 4 in the first part of the tables). In addition, the pseudo-R^2 statistics, which measure the joint significance of the matching variables in the Probit model, decline substantially after matching, with the largest decrease observed in the community service sample (from 0.259 to 0.009) and the smallest in the student exchange sample.

Table 3. Balancing Test Before and After Matching for Student Exchange Program

Variable	Sample	Mean		Bias (%)	t-test	
		Treated	Control		t-stat	p>t
	(1)	(2)	(3)	(4)	(5)	(6)
gender (if female)	Unmatched	0.625	0.642	-3.600	-0.42	0.678
	Matched	0.625	0.636	-2.400	-0.19	0.847
age	Unmatched	25.691	25.890	-4.800	-0.59	0.556
	Matched	25.691	25.848	-3.800	-0.30	0.762
marital status (if married)	Unmatched	0.176	0.199	-5.900	-0.670	0.502
	Matched	0.176	0.189	-3.300	-0.270	0.787
type of school (if private)	Unmatched	0.389	0.468	-15.900	-1.820	0.069
	Matched	0.389	0.446	-11.600	-0.950	0.341
Training (if yes)	Unmatched	0.566	0.544	4.400	0.500	0.616
	Matched	0.566	0.549	3.300	0.270	0.785
On-going training (if yes)	Unmatched	0.095	0.034	24.800	3.760	0.000
	Matched	0.095	0.047	19.700	1.550	0.123
Computer use (if yes)	Unmatched	0.845	0.803	11.000	1.220	0.223
	Matched	0.845	0.823	5.700	0.480	0.631
Smartphone use (if yes)	Unmatched	0.985	0.997	-13.200	-2.650	0.008
	Matched	0.985	0.995	-11.3	-0.89	0.375
Internet use (if yes)	Unmatched	0.992	0.991	1.4	0.16	0.872
	Matched	0.992	0.993	-0.8	-0.07	0.941
Region (if rural)	Unmatched	0.544	0.380	33.3	3.89	0.000
	Matched	0.544	0.431	22.8	1.86	0.064
Community Services (if yes)	Unmatched	0.617	0.233	84.3	10.44	0.000
	Matched	0.617	0.336	61.5	4.81	0.000
Internship (if yes)	Unmatched	0.838	0.376	107.2	11.04	0.000
	Matched	0.838	0.505	77.2	6.23	0.000

Notes: The balancing test also includes dummy variables for field of study and province; however, these results are omitted from the table for brevity and are available upon request. * if B>25%, R outside [0.5; 2]. *Source*: Authors' calculation from *Sakernas* 2024.

Table 4. Balancing Test Before and After Matching for Community Service Program

Variable	Sample	Mean		Bias	t-test	
		Treated	Control	(%)	t-stat	p>t
gender (if female)	Unmatched	0.660	0.637	4.8	1.59	0.112
	Matched	0.659	0.653	1.2	0.34	0.737
age	Unmatched	24.765	26.238	-41.8	-12.77	0.000
	Matched	24.767	24.898	-3.7	-1.34	0.181
marital status (if married)	Unmatched	0.114	0.225	-30.1	-9.31	0.000
	Matched	0.114	0.121	-1.8	-0.57	0.570
type of school (if private)	Unmatched	0.418	0.475	-11.4	-3.77	0.000
	Matched	0.418	0.443	-5.0	-1.34	0.181
Training (if yes)	Unmatched	0.585	0.535	10.0	3.30	0.001
	Matched	0.586	0.570	3.1	0.82	0.411
On-going training (if yes)	Unmatched	0.042	0.034	4.3	1.46	0.145
	Matched	0.042	0.043	-0.6	-0.15	0.879
Computer use (if yes)	Unmatched	0.839	0.792	12.2	3.92	0.000
	Matched	0.839	0.838	0.3	0.07	0.942
Smartphone use (if yes)	Unmatched	0.997	0.996	2.0	0.62	0.534
	Matched	0.997	0.997	1.5	0.42	0.677
Internet use (if yes)	Unmatched	0.992	0.990	1.8	0.57	0.569
	Matched	0.992	0.994	-2.3	-0.70	0.487
Region (if rural)	Unmatched	0.424	0.374	10.3	3.42	0.001
	Matched	0.424	0.422	0.3	0.09	0.930
Student Exchange (if yes)	Unmatched	0.058	0.011	25.8	10.49	0.000
	Matched	0.057	0.039	10.0	2.28	0.023
Internship (if yes)	Unmatched	0.811	0.252	135.5	43.58	0.000
	Matched	0.811	0.802	2.4	0.66	0.507

Notes: The balancing test also includes dummy variables for field of study and province; however, these results are omitted from the table for brevity and are available upon request. * if B>25%, R outside [0.5; 2]. *Source*: Authors' calculation from *Sakernas* 2024.

Table 5. Balancing Test Before and After Matching for Internship Program

Variable	Sample	Mean		Bias	t-test	
		Treate	Control		t-stat	p>t
gender (if female)	Unmatched	0.644	0.641	0.8	0.30	0.762
	Matched	0.645	0.645	-0.1	-0.03	0.978
age	Unmatched	24.854	26.533	-46.5	-16.74	0.000
	Matched	24.875	24.979	-2.9	-1.42	0.156
marital status (if	Unmatched	0.123	0.246	-31.9	-11.66	0.000
	Matched	0.125	0.119	1.7	0.65	0.513
type of school (if private)	Unmatched	0.452	0.467	-2.9	-1.07	0.284
	Matched	0.452	0.469	-3.3	-1.11	0.267
Training (if yes)	Unmatched	0.573	0.531	8.5	3.21	0.001
	Matched	0.571	0.552	3.9	1.32	0.185
On-going training (if yes)	Unmatched	0.045	0.030	8.3	3.19	0.001
	Matched	0.043	0.035	4.1	1.34	0.181
Computer use (if yes)	Unmatched	0.823	0.792	7.9	2.94	0.003
	Matched	0.822	0.823	-0.1	-0.04	0.972
Smartphone use (if yes)	Unmatched	0.996	0.997	-1.9	-0.71	0.478
	Matched	0.996	0.998	-3.1	-1.08	0.280
Internet use (if yes)	Unmatched	0.991	0.990	0.4	0.14	0.886
	Matched	0.991	0.994	-3.7	-1.41	0.159
Region (if rural)	Unmatched	0.403	0.372	7.4	2.80	0.005
	Matched	0.403	0.405	-0.4	-0.13	0.895
Community Services (if	Unmatched	0.505	0.073	108.1	43.58	0.000

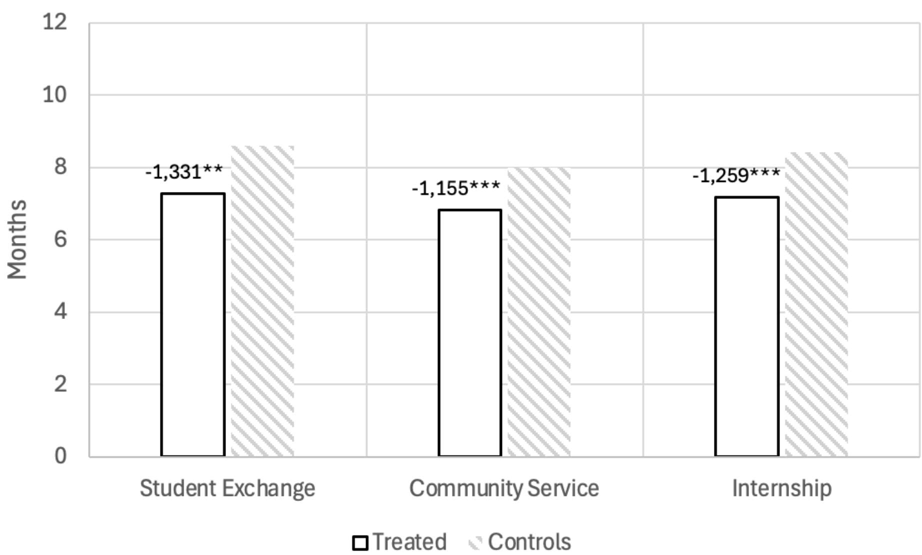
Variable	Sample	Mean		Bias	t-test	
		Treate	Control		t-stat	p>t
	Matched	0.492	0.483	2.2	0.58	0.561
Student Exchange (if	Unmatched	0.049	0.006	26.7	11.04	0.000
	Matched	0.024	0.021	1.8	0.66	0.512

Notes: The balancing test also includes dummy variables for field of study and province; however, these results are omitted from the table for brevity and are available upon request. * if B>25%, R outside [0.5; 2].
Source: Authors' calculation from *Sakernas* 2024.

Figure 4 presents the average treatment effect for the treated (ATT) for each SM program after implementing the kernel matching. For comparison, Appendix 3 provides the Ordinary Least Squares (OLS) results when using similar pre-treatment covariates as control variables. Our results show that the OLS estimations tend to overestimate the effect of the programmes (particularly the community service and internship) on the first job waiting time after graduation, likely due to residual selection bias that is not fully addressed.

As a robustness check, we also use the other matching algorithms within the PSM. The estimation results using the Gaussian kernel method show more consistent and statistically significant effects than those from other matching approaches. This can be explained by the fact that kernel matching incorporates a larger set of control units, assigning declining weights smoothly with respect to their distance, thereby reducing the variance of the estimates. Therefore, the t-statistics tend to be larger. However, this method may introduce a small bias because it also includes relatively distant control units, albeit with very small weights (Caliendo and Kopeinig, 2008). Therefore, the findings obtained through kernel matching can be considered more efficient but should still be interpreted with caution.

Figure 4. Effect of SM Programmes on Graduates' Waiting Time for First Job After Kernel Matching



Notes: The bar charts show the average treatment of the treated (ATT). *** p < 0.01, ** p < 0.05, * p < 0.1.
Source: Authors' calculations from *Sakernas* 2024.

The average treatment effects on the treated (ATTs) of SM programmes are statistically significant in reducing the waiting time for the first job after graduation, as indicated by the kernel matching results. These findings are consistent with signalling theory, which suggests that participation in structured programmes serves as a credible, observable signal of productive traits to employers who cannot directly observe graduates' competencies. Compared with non-participants, those who joined the student exchange program experienced a shorter waiting time to secure employment by 1,331 months (approximately 40 days). Participation in the community service program shortened unemployment by 1,155 months (approximately 35 days), while engagement in the internship program reduced the waiting period by about 1,259 months (approximately 38 days).

These findings are consistent with prior research conducted at the international level, including Rothwell et al. (2023), Storgård (2025) in the student exchange program, and Di Meglio et al (2022) and Margaryan et al (2022) in the internship program. Participation in SM programmes serves as a signal to employers of students' teamwork, adaptability, and leadership, which are competencies that are difficult for employers to observe directly but are highly valued in the labour market. Consistent with signalling theory and previous studies, SM participation functions as a credible observable indicator of these productive traits, helping employers screen candidates more effectively. Students who join such programmes therefore send a positive signal about their workplace readiness, which may reduce the time needed to secure their first job.

Our findings indicate that student exchange participation has the strongest effect in reducing waiting time for the first job, likely because it signals additional skills such as language proficiency, intercultural competence, and independence (Petzold in d'Hombres & Schnepf, 2021; Rothwell et al. 2023; Storgård, 2025). Although our data do not allow us to distinguish between domestic and international exchange participants, it is plausible that a portion of students in this category participated in international programmes. Prior research highlights that such programmes foster personal growth, confidence, and cultural competence (Rothwell et al., 2023), and that graduates with international mobility experience tend to find employment more quickly than those without (Wiers-Jenssen and Støren, 2021; Yue et al., 2024; Knutsen, Wiborg and Wiers-Jenssen, 2025). These factors may partly explain the stronger signalling effect observed for student exchange participants in our study.

Conclusion

This research investigates the impact of student mobility (SM) programmes, namely student exchange, community service, and internships, on Indonesian graduates' waiting time for their first job. While each program develops similar soft skills, they convey different signalling values to employers. Existing global evidence regarding this topic often shows mixed results and lacks comparative analysis across programmes, while evidence in the Indonesian context is largely absent. By using individual participation data in SM programmes from the 2024 National Labour Force Survey (*Sakernas*) and applying the Propensity Score Matching (PSM) method, this study addresses these gaps, providing quantitative evidence on how different SM programmes may shape employment outcomes and offering insights for policy design in the Indonesian context.Our results show that SM programmes have significant effects in reducing waiting time for their first job after graduation.

Participation in student exchange and community service programmes shortens waiting time for the first job by approximately 1.331 months (around 40 days) and 1.155 months (around 35 days), respectively, compared to non-participants. Similarly, internship experience reduces waiting time for the first job by about 1.259 months (around 38 days). These findings suggest that SM programmes are effective mechanisms for facilitating faster school-to-work transitions. The student participation in such programmes appears to serve as a credible signal to employers regarding the skills required for productivity and employability. Therefore, government and universities should expand opportunities, through increased funding and quotas, for students to participate student exchange, community service, and internships.

This policy recommendation aligns with the *Merdeka Belajar–Kampus Merdeka* (MBKM) program and the emphasis on international exposure articulated in the Ministry of Education, Science, and Technology Regulation No. 39/2025. At the institutional level, universities should move beyond treating SM programmes as optional enrichment activities and instead position them as a core component of the academic learning pathway. This can be achieved by integrating SM participation into the curriculum with formal credit recognition and clear learning outcomes aligned with labour market needs. In addition, strengthening partnerships with industry and international institutions is essential to ensure that SM experiences remain relevant and provide meaningful exposure.

To improve accessibility, universities need to reduce barriers to participation by offering flexible academic arrangements and simplifying administrative processes. Finally, universities should strengthen the signalling value of SM programmes by systematically documenting students' competencies, thereby making these experiences more visible and credible to employers. This study points to several promising directions for future research. With richer data, researchers could take a closer look at program details such as how long students participate, whether the schemes are national or international, and what specific skills students gain. Better data collection by Statistics Indonesia would make this possible and allow for meaningful analysis. Future studies could also extend beyond the basic pre-treatment characteristics used here and apply stronger methods, such as Difference-in-Differences (DID), instrumental variables (IV), or a combination of PSM and DID, to obtain a clearer picture of causality. Finally, broadening the focus beyond fresh graduate's waiting time for their first job to include things like earnings, job type, and job quality would help us understand more fully how student mobility programmes shape students' careers and lives after graduation.

AI declaration

The authors declare that artificial intelligence (AI) tools were used solely to assist in language refinement, grammar checking, and improving the clarity of writing. The use of AI did not influence the research design, data collection, data analysis, interpretation of results, or the development of conclusions. All intellectual contributions, including conceptualization, methodology, analysis, and final content, remain the full responsibility of the authors.

Conflict Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper. The research was conducted independently without any financial, commercial, or personal relationships that could be construed as a potential conflict of interest.

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Appendix 1. Summary of Literature for Competencies

Skills Learned	Community Services	Internship	Student Exchange
Teamwork and Collaboration	(Fede, Gorman and Cimini, 2018; Mtawa, Fongwa and Wilson-Strydom, 2021; Hernandez and Newman, 2006, cited in Jelinčić, Baturina and Franić, 2022)	(Kapareliotis, Voutsina and Patsiotis, 2019; Anjum, 2020; Jackson, O'Brien and Richards, 2023; Hassouna, Zeinab and Zaazou, 2024; Pianda et al., 2024; Tsambou et al., 2024; Musa, Nurhayati and Boriboon, 2025; Tsai et al., 2017, cited in Pantaruk et al., 2025)	(Jones, 2013, cited in Wiers-Jenssen and Støren, 2021; Wiers-Jenssen and Støren, 2021; Storgård, 2025)
Communication and Interpersonal	(Reed-Bouley, Wernli and Sather, 2012; Ma Hok-ka, Chan Wing-fung and Chan Cheung-ming, 2016; Fede, Gorman and Cimini, 2018; Weiler et al., 2013, cited in Schulzetenberg et al., 2020; Mtawa, Fongwa and Wilson-Strydom, 2021; Keen and Hall, 2009, cited in Jelinčić, Baturina and Franić, 2022; Chesbrough, 2011, cited in Jelinčić, Baturina and Franić, 2022)	(Kapareliotis, Voutsina and Patsiotis, 2019; Anjum, 2020; Baert *et al.*, 2021; Jackson, O'Brien and Richards, 2023; Hassouna, Zeinab and Zaazou, 2024; Mseleku, 2024; Pianda *et al.*, 2024; Tsambou *et al.*, 2024; Kwan *et al.*, 2025; Musa, Nurhayati and Boriboon, 2025; Pantaruk *et al.*, 2025)	(Di Pietro, 2013; Wiers-Jenssen and Try, 2005, cited in Iriondo, 2020; Teichler, 2011, cited in Iriondo, 2020; d'Hombres and Schnepf, 2021; Netz and Grüttner, 2021; Rizzi, Grassetti and Attanasio, 2021; Van Mol, Caarls and Souto-Otero, 2021; Rothwell et al., 2023; Storgård, 2025)
Problem Solving and Critical Thinking	(Reed-Bouley et al. 2012; Hokka et al. 2016; Govekar and Rishi, 2007, cited in Jelinčić, Baturina and Franić, 2022; Keen and Hall, 2009, cited in Jelinčić, Baturina and Franić, 2022; Chesbrough, 2011, cited in Jelinčić, Baturina and Franić, 2022)	(Kapareliotis, Voutsina and Patsiotis, 2019; Anjum, 2020; Jackson, O'Brien and Richards, 2023; Hassouna, Zeinab and Zaazou, 2024; Pianda *et al.*, 2024; Pantaruk *et al.*, 2025)	(Iriondo, 2020; Rizzi, Grassetti and Attanasio, 2021; Genkova and Kruse, 2020, cited in Storgård, 2025)
Leadership and Professionalism	(Matthews, Dorfman and Wu, 2015; Ma Hok-ka, Chan Wing-fung and Chan Cheung-ming, 2016; Robles, 2012, cited in Fede, Gorman and Cimini, 2018; Weiler et al., 2013, cited in Schulzetenberg et al., 2020; Mtawa, Fongwa and Wilson-Strydom, 2021; Hernandez and Newman, 2006, cited in Jelinčić, Baturina and Franić, 2022)	(Kapareliotis, Voutsina and Patsiotis, 2019; Anjum, 2020; Jackson, O'Brien and Richards, 2023; Hassouna, Zeinab and Zaazou, 2024; Pianda *et al.*, 2024; Kwan *et al.*, 2025; Pantaruk *et al.*, 2025)	(Zimmermann and Neyer, 2013, cited in Netz and Grüttner, 2021; Rizzi, Grassetti and Attanasio, 2021; Van Mol, Caarls and Souto-Otero, 2021; Jones, 2013, cited in Wiers-Jenssen and Støren, 2021; European Commission, 2016, cited in Granja and Visentin, 2024; Storgård, 2025)

Skills Learned	Community Services	Internship	Student Exchange
Adaptability	(Matthews, Dorfman and Wu, 2015; Ma Hok-ka, Chan Wing-fung and Chan Cheung-ming, 2016; Kuh et al., 2011, cited in Fede, Gorman and Cimini, 2018; Weiler et al., 2013, cited in Schulzetenberg et al., 2020)	(Anjum, 2020; Baert *et al.*, 2021; Jackson, O'Brien and Richards, 2023; Hassouna, Zeinab and Zaazou, 2024; Tsambou *et al.*, 2024; Kwan *et al.*, 2025; Musa, Nurhayati and Boriboon, 2025; Pantaruk *et al.*, 2025)	(Salisbury et al., 2013, cited in d'Hombres and Schnepf, 2021; d'Hombres and Schnepf, 2021; Netz and Grüttner, 2021; Rizzi, Grassetti and Attanasio, 2021; Rothwell et al., 2023; Storgård, 2025)

Appendix 2. Operational Definition of Variables

No	Variable Name	Description
		Dependent Variable
1	Unemployment Duration	The length of time (in months) an individual remains unemployed after completing undergraduate study
		Treatment Variables
1	Student Exchange	A dummy variable indicating whether the respondent participated in a student exchange program (1 = yes, 0 = no)
2	Community Service	A dummy variable indicating whether the respondent participated in a community service program (1 = yes, 0 = no)
3	Internship	A dummy variable indicating whether the respondent participated in an internship program (1 = yes, 0 = no)
		Control Variables
1	Gender (if female)	A dummy variable for gender (1 = female, 0 = male)
2	Age	The age of the respondent (in years)
3	Marital Status (if married)	A dummy variable for marital status (1 = married, 0 = otherwise)
4	Type of School (if private)	A dummy variable indicating type of school (1 = private, 0 = public)
5	Training (if yes)	A dummy variable indicating whether the respondent ever attended training (1 = yes, 0 = no)
6	On-going training (if yes)	A dummy variable indicating whether the respondent was still attending training at the time of the survey (1 = yes, 0 = no)
7	Computer use (if yes)	A dummy variable indicating whether the respondent can use a computer (1 = yes, 0 = no)

No	Variable Name	Description
8	Smartphone use (if yes)	A dummy variable indicating whether the respondent can use a smartphone (1 = yes, 0 = no)
9	Internet use (if yes)	A dummy variable indicating whether the respondent can use the internet (1 = yes, 0 = no)
10	Region (if rural)	A dummy variable indicating whether the respondent resides in a rural area (1 = rural, 0 = urban)
11	Field of Study	Field of Study is a categorical variable coded as: 1 = Mathematics and Natural Sciences, 2 = Plant Science, 3 = Animal Science, 4 = Medical Science, 5 = Health Science, 6 = Engineering, 7 = Language Studies, 8 = Economics, 9 = Social Sciences and Humanities, 10 = Religion and Philosophy, 11 = Arts, Design and Media, and 12 = Education Science.
12	Provinces	Provinces is a categorical variable coded as: 11 = Aceh, 12 = North Sumatra, 13 = West Sumatra, 14 = Riau, 15 = Jambi, 16 = South Sumatra, 17 = Bengkulu, 18 = Lampung, 19 = Bangka Belitung Islands, 21 = Riau Islands, 31 = DKI Jakarta, 32 = West Java, 33 = Central Java, 34 = Special Region of Yogyakarta, 35 = East Java, 36 = Banten, 51 = Bali, 52 = West Nusa Tenggara, 53 = East Nusa Tenggara, 61 = West Kalimantan, 62 = Central Kalimantan, 63 = South Kalimantan, 64 = East Kalimantan, 65 = North Kalimantan, 71 = North Sulawesi, 72 = Central Sulawesi, 73 = South Sulawesi, 74 = Southeast Sulawesi, 75 = Gorontalo, 76 = West Sulawesi, 81 = Maluku, 82 = North Maluku, 91 = West Papua, 92 = Southwest Papua, and 94 = Papua.

Appendix 3. Effect of SM Programmes on Graduates' Waiting Time for First Job (OLS)

Variable	(1) Std Exchange	(2) Community Service	(3) Internship
Student Exchange (1= yes)	-1.694**		
	(0.673)		
Community Service (1=yes)		-2.578***	
		(0.250)	
Internship (1=yes)			-2.614***
			(0.240)
Constant	6.078*	7.733**	8.720***
	(3.401)	(3.304)	(3.252)
Gender (if female)	0.232	0.230	0.192
	(0.270)	(0.268)	(0.268)
Age	0.272***	0.233***	0.210***
	(0.046)	(0.045)	(0.044)
Marital Status (if married)	0.353	0.169	0.099
	(0.380)	(0.379)	(0.376)
Type of school	0.299	0.240	0.297
	(0.259)	(0.257)	(0.256)
Field of Study (1=Math and Natural Sciences)			
Plant Science	0.491	0.456	0.597
	(0.984)	(0.983)	(0.980)
Animal Science	0.139	0.196	0.341
	(1.112)	(1.100)	(1.092)
Medical Science	-1.631	-1.403	-1.085
	(1.373)	(1.376)	(1.377)
Health Science	-0.032	-0.063	0.180
	(0.745)	(0.744)	(0.743)
Engineering	-0.463	-0.582	-0.368
	(0.723)	(0.722)	(0.719)
Language Studies	-1.151	-1.155	-1.053
	(0.834)	(0.833)	(0.834)
Economics	-0.778	-0.885	-0.721
	(0.688)	(0.688)	(0.685)
Social Sciences and Humanities	-0.316	-0.375	-0.249
	(0.713)	(0.713)	(0.710)
Religion and Philosophy	-0.499	-0.285	-0.323
	(0.936)	(0.936)	(0.926)
Arts Design and Media	1.587	1.334	1.744
	(2.056)	(2.009)	(2.053)
Education Science	-1.419**	-1.469**	-1.289*
	(0.681)	(0.681)	(0.678)
Region (if rural)	-0.062	0.026	0.060
	(0.279)	(0.278)	(0.276)

Variable	(1) Std Exchange	(2) Community Service	(3) Internship
Province (1 = Aceh)			
North Sumatra	-1.254	-1.531*	-1.258
	(0.798)	(0.789)	(0.787)
West Sumatra	-1.270	-1.534*	-1.232
	(0.811)	(0.801)	(0.803)
Riau	-2.065**	-2.362**	-1.990**
	(0.947)	(0.939)	(0.940)
Jambi	-1.036	-1.428	-1.047
	(0.950)	(0.953)	(0.943)
South Sumatra	-2.089**	-2.363***	-1.950**
	(0.893)	(0.892)	(0.891)
Bengkulu	-2.029**	-2.288**	-2.048**
	(0.908)	(0.896)	(0.892)
Lampung	-1.031	-1.289	-1.170
	(1.054)	(1.043)	(1.034)
Bangka Belitung Islands	-2.882**	-3.336***	-2.937**
	(1.172)	(1.155)	(1.146)
Riau Islands	-2.126*	-2.448**	-2.303*
	(1.224)	(1.231)	(1.218)
DKI Jakarta	-3.606***	-4.114***	-3.713***
	(0.885)	(0.879)	(0.877)
West Java	-1.821**	-2.150***	-1.804**
	(0.806)	(0.797)	(0.794)
Central Java	-2.646***	-2.670***	-2.545***
	(0.777)	(0.765)	(0.770)
Special Region of Yogyakarta	-2.511**	-2.738**	-2.919**
	(1.180)	(1.162)	(1.184)
East Java	-3.100***	-3.276***	-2.995***
	(0.714)	(0.704)	(0.705)
Banten	-2.307**	-2.722**	-2.338**
	(1.063)	(1.057)	(1.054)
Bali	-3.380***	-3.756***	-3.554***
	(0.911)	(0.898)	(0.904)
West Nusa Tenggara	-1.834*	-1.823*	-1.908*
	(0.989)	(0.971)	(0.984)
East Nusa Tenggara	0.668	0.511	0.807
	(0.857)	(0.840)	(0.843)
West Kalimantan	-1.763	-2.130*	-1.546
	(1.114)	(1.094)	(1.104)
Central Kalimantan	-0.816	-1.142	-0.960
	(1.302)	(1.286)	(1.292)
South Kalimantan	-1.159	-1.717	-1.092
	(1.078)	(1.065)	(1.067)
East Kalimantan	-1.264	-1.577	-1.187
	(0.988)	(0.980)	(0.974)
North Kalimantan	0.750	0.308	0.807

Variable	(1) Std Exchange	(2) Community Service	(3) Internship
	(1.324)	(1.307)	(1.304)
North Sulawesi	0.034	-0.184	0.013
	(0.969)	(0.949)	(0.947)
Central Sulawesi	0.868	0.431	0.685
	(1.269)	(1.246)	(1.243)
South Sulawesi	0.624	0.350	0.534
	(0.859)	(0.853)	(0.853)
Southeast Sulawesi	-1.455*	-1.706**	-1.550*
	(0.817)	(0.804)	(0.810)
Gorontalo	1.211	1.291	1.232
	(1.378)	(1.385)	(1.378)
West Sulawesi	-1.287	-1.636	-1.562
	(1.323)	(1.299)	(1.309)
Maluku	-1.690	-1.811*	-1.639
	(1.077)	(1.072)	(1.074)
North Maluku	-0.033	-0.179	-0.013
	(1.149)	(1.147)	(1.134)
West Papua	-0.375	-0.729	-0.396
	(1.474)	(1.451)	(1.451)
Southwest Papua	-2.852**	-2.836**	-2.564*
	(1.382)	(1.362)	(1.362)
Papua	-0.822	-1.066	-0.678
	(1.115)	(1.113)	(1.089)
Training (if yes)	0.088	0.186	0.190
	(0.250)	(0.248)	(0.247)
On-going training (if yes)	-0.992	-1.001*	-0.814
	(0.606)	(0.595)	(0.599)
Computer use (if yes)	-0.040	0.044	-0.015
	(0.336)	(0.334)	(0.333)
Smartphone use (if yes)	-1.954	-1.744	-2.144
	(3.069)	(3.000)	(2.944)
Internet use (if yes)	-0.408	-0.463	-0.453
	(1.544)	(1.541)	(1.512)
Observations	5,963	5,963	5,963
R-squared	0.038	0.050	0.055

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. *Source*: Authors' calculations from *Sakernas* 2024.